EXHIBIT 6

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Journal of Economic Literature
Vol. XXXV (March 1997), pp. 13–39

Event Studies in Economics and Finance

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Thanks to John Campbell, Bruce Grundy, Andrew Lo, and two anonymous referees for helpful comments and discussion. Research support from the Rodney L. White Center for Financial Research is gratefully acknowledged.

1. *Introduction*

ECONOMISTS are frequently asked to measure the effects of an economic event on the value of firms. On the surface this seems like a difficult task, but a measure can be constructed easily using an event study. Using financial market data, an event study measures the impact of a specific event on the value of a firm. The usefulness of such a study comes from the fact that, given rationality in the marketplace, the effects of an event will be reflected immediately in security prices. Thus a measure of the event's economic impact can be constructed using security prices observed over a relatively short time period. In contrast, direct productivity related measures may require many months or even years of observation.

The event study has many applications. In accounting and finance research, event studies have been applied to a variety of firm specific and economy wide events. Some examples include mergers and acquisitions, earnings announcements, issues of new debt or equity, and announcements of macroeconomic variables such as the trade deficit.[1] However, applications in other fields are also abundant. For example, event studies are used in the field of law and economics to measure the impact on the value of a firm of a change in the regulatory environment (see G. William Schwert 1981) and in legal liability cases event studies are used to assess damages (see Mark Mitchell and Jeffry Netter 1994). In the majority of applications, the focus is the effect of an event on the price of a particular class of securities of the firm, most often common equity. In this paper the methodology is discussed in terms of applications that use common equity. However, event studies can be applied using debt securities with little modification.

Event studies have a long history. Perhaps the first published study is James Dolley (1933). In this work, he examines the price effects of stock splits, studying nominal price changes at the time of the split. Using a sample of 95 splits from 1921 to 1931, he finds that the price in-

[1] The first three examples will be discussed later in the paper. Grant McQueen and Vance Roley (1993) provide an illustration of the fourth using macroeconomic news announcements.

creased in 57 of the cases and the price declined in only 26 instances. Over the decades from the early 1930s until the late 1960s the level of sophistication of event studies increased. John H. Myers and Archie Bakay (1948), C. Austin Barker (1956, 1957, 1958), and John Ashley (1962) are examples of studies during this time period. The improvements included removing general stock market price movements and separating out confounding events. In the late 1960s seminal studies by Ray Ball and Philip Brown (1968) and Eugene Fama et al. (1969) introduced the methodology that is essentially the same as that which is in use today. Ball and Brown considered the information content of earnings, and Fama et al. studied the effects of stock splits after removing the effects of simultaneous dividend increases.

In the years since these pioneering studies, a number of modifications have been developed. These modifications relate to complications arising from violations of the statistical assumptions used in the early work and relate to adjustments in the design to accommodate more specific hypotheses. Useful papers which deal with the practical importance of many of the complications and adjustments are the work by Stephen Brown and Jerold Warner published in 1980 and 1985. The 1980 paper considers implementation issues for data sampled at a monthly interval and the 1985 paper deals with issues for daily data.

In this paper, event study methods are reviewed and summarized. The paper begins with discussion of one possible procedure for conducting an event study in Section 2. Section 3 sets up a sample event study which will be used to illustrate the methodology. Central to an event study is the measurement of an abnormal stock return. Section 4 details the first step—measuring the normal performance—and Section 5 follows with the necessary tools for calculating an abnormal return, making statistical inferences about these returns, and aggregating over many event observations. The null hypothesis that the event has no impact on the distribution of returns is maintained in Sections 4 and 5. Section 6 discusses modifying this null hypothesis to focus only on the mean of the return distribution. Section 7 presents analysis of the power of an event study. Section 8 presents nonparametric approaches to event studies which eliminate the need for parametric structure. In some cases theory provides hypotheses concerning the relation between the magnitude of the event abnormal return and firm characteristics. Section 9 presents a cross-sectional regression approach that is useful to investigate such hypotheses. Section 10 considers some further issues relating event study design and the paper closes with the concluding discussion in Section 11.

2. *Procedure for an Event Study*

At the outset it is useful to briefly discuss the structure of an event study. This will provide a basis for the discussion of details later. While there is no unique structure, there is a general flow of analysis. This flow is discussed in this section.

The initial task of conducting an event study is to define the event of interest and identify the period over which the security prices of the firms involved in this event will be examined—the event window. For example, if one is looking at the information content of an earnings with daily data, the event will be the earnings announcement and the event window will include the one day of the announcement. It is customary to define the event window to be larger than the specific period of interest. This permits examination of periods surrounding the

event. In practice, the period of interest is often expanded to multiple days, including at least the day of the announcement and the day after the announcement. This captures the price effects of announcements which occur after the stock market closes on the announcement day. The periods prior to and after the event may also be of interest. For example, in the earnings announcement case, the market may acquire information about the earnings prior to the actual announcement and one can investigate this possibility by examining pre-event returns.

After identifying the event, it is necessary to determine the selection criteria for the inclusion of a given firm in the study. The criteria may involve restrictions imposed by data availability such as listing on the New York Stock Exchange or the American Stock Exchange or may involve restrictions such as membership in a specific industry. At this stage it is useful to summarize some sample characteristics (e.g., firm market capitalization, industry representation, distribution of events through time) and note any potential biases which may have been introduced through the sample selection.

Appraisal of the event's impact requires a measure of the abnormal return. The abnormal return is the actual ex post return of the security over the event window minus the normal return of the firm over the event window. The normal return is defined as the expected return without conditioning on the event taking place. For firm i and event date τ the [illegible]mal return is

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau) \qquad (1)$$

[illegible] $R_{i\tau}$, and $E(R_{i\tau}|X_\tau)$ are the ab[illegible] actual, and normal returns re[illegible] time period τ. X_τ is the [illegible] information for the normal [illegible] There are two common choices for modeling the normal return—the *constant mean return model* where X_τ is a constant, and the *market model* where X_τ is the market return. The constant mean return model, as the name implies, assumes that the mean return of a given security is constant through time. The market model assumes a stable linear relation between the market return and the security return.

Given the selection of a normal performance model, the estimation window needs to be defined. The most common choice, when feasible, is using the period prior to the event window for the estimation window. For example, in an event study using daily data and the market model, the market model parameters could be estimated over the 120 days prior to the event. Generally the event period itself is not included in the estimation period to prevent the event from influencing the normal performance model parameter estimates.

With the parameter estimates for the normal performance model, the abnormal returns can be calculated. Next comes the design of the testing framework for the abnormal returns. Important considerations are defining the null hypothesis and determining the techniques for aggregating the individual firm abnormal returns.

The presentation of the empirical results follows the formulation of the econometric design. In addition to presenting the basic empirical results, the presentation of diagnostics can be fruitful. Occasionally, especially in studies with a limited number of event observations, the empirical results can be heavily influenced by one or two firms. Knowledge of this is important for gauging the importance of the results.

Ideally the empirical results will lead to insights relating to understanding the sources and causes of the effects (or lack

of effects) of the event under study. Additional analysis may be included to distinguish between competing explanations. Concluding comments complete the study.

3. *An Example of an Event Study*

The Financial Accounting Standards Board (FASB) and the Securities Exchange Commission strive to set reporting regulations so that financial statements and related information releases are informative about the value of the firm. In setting standards, the information content of the financial disclosures is of interest. Event studies provide an ideal tool for examining the information content of the disclosures.

In this section the description of an example selected to illustrate event study methodology is presented. One particular type of disclosure—quarterly earnings announcements—is considered. The objective is to investigate the information content of these announcements. In other words, the goal is to see if the release of accounting information provides information to the marketplace. If so there should be a correlation between the observed change of the market value of the company and the information.

The example will focus on the quarterly earnings announcements for the 30 firms in the Dow Jones Industrial Index over the five-year period from January 1989 to December 1993. These announcements correspond to the quarterly earnings for the last quarter of 1988 through the third quarter of 1993. The five years of data for 30 firms provide a total sample of 600 announcements. For each firm and quarter, three pieces of information are compiled: the date of the announcement, the actual earnings, and a measure of the expected earnings. The source of the date of the announcement is Datastream, and the source of the actual earnings is Compustat.

If earnings announcements convey information to investors, one would expect the announcement impact on the market's valuation of the firm's equity to depend on the magnitude of the unexpected component of the announcement. Thus a measure of the deviation of the actual announced earnings from the market's prior expectation is required. For constructing such a measure, the mean quarterly earnings forecast reported by the Institutional Brokers Estimate System (I/B/E/S) is used to proxy for the market's expectation of earnings. I/B/E/S compiles forecasts from analysts for a large number of companies and reports summary statistics each month. The mean forecast is taken from the last month of the quarter. For example, the mean third quarter forecast from September 1990 is used as the measure of expected earnings for the third quarter of 1990.

To facilitate the examination of the impact of the earnings announcement on the value of the firm's equity, it is essential to posit the relation between the information release and the change in value of the equity. In this example the task is straightforward. If the earnings disclosures have information content, higher than expected earnings should be associated with increases in value of the equity and lower than expected earnings with decreases. To capture this association, each announcement is assigned to one of three categories: good news, no news, or bad news. Each announcement is categorized using the deviation of the actual earnings from the expected earnings. If the actual exceeds expected by more than 2.5 percent the announcement is designated as good news, and if the actual is more than 2.5 percent less than expected the announcement is designated as bad news. Those announce-

ments where the actual earnings is in the 5 percent range centered about the expected earnings are designated as no news. Of the 600 announcements, 189 are good news, 173 are no news, and the remaining 238 are bad news.

With the announcements categorized, the next step is to specify the parameters of the empirical design to analyze the equity return, i.e., the percent change in value of the equity. It is necessary to specify a length of observation interval, an event window, and an estimation window. For this example the interval is set to one day, thus daily stock returns are used. A 41-day event window is employed, comprised of 20 pre-event days, the event day, and 20 post-event days. For each announcement the 250 trading day period prior to the event window is used as the estimation window. After presenting the methodology of an event study, this example will be drawn upon to illustrate the execution of a study.

4. *Models for Measuring Normal Performance*

A number of approaches are available to calculate the normal return of a given security. The approaches can be loosely grouped into two categories—statistical and economic. Models in the first category follow from statistical assumptions concerning the behavior of asset returns and do not depend on any economic arguments. In contrast, models in the second category rely on assumptions concerning investors' behavior and are not based solely on statistical assumptions. It should, however, be noted that to use economic models in practice it is necessary to add statistical assumptions. Thus the potential advantage of economic models is not the absence of statistical assumptions, but the opportunity to calculate more precise measures of the normal return using economic restrictions.

For the statistical models, the assumption that asset returns are jointly multivariate normal and independently and identically distributed through time is imposed. This distributional assumption is sufficient for the constant mean return model and the market model to be correctly specified. While this assumption is strong, in practice it generally does not lead to problems because the assumption is empirically reasonable and inferences using the normal return models tend to be robust to deviations from the assumption. Also one can easily modify the statistical framework so that the analysis of the abnormal returns is autocorrelation and heteroskedasticity consistent by using a generalized method-of-moments approach.

A. *Constant Mean Return Model*

Let μ_i be the mean return for asset i. Then the constant mean return model is

$$R_{it} = \mu_i + \zeta_{it} \tag{2}$$

$$E(\zeta_{it}) = 0 \qquad \operatorname{var}(\zeta_{it}) = \sigma^2_{\zeta_i}.$$

where R_{it} is the period-t return on security i and ζ_{it} is the time period t disturbance term for security i with an expectation of zero and variance $\sigma^2_{\zeta_i}$.

Although the constant mean return model is perhaps the simplest model, Brown and Warner (1980, 1985) find it often yields results similar to those of more sophisticated models. This lack of sensitivity to the model can be attributed to the fact that the variance of the abnormal return is frequently not reduced much by choosing a more sophisticated model. When using daily data the model is typically applied to nominal returns. With monthly data the model can be applied to real returns or excess returns (the return in excess of the nominal risk free return generally measured using the U.S. Treasury Bill with one month to maturity) as well as nominal returns.

B. *Market Model*

The market model is a statistical model which relates the return of any given security to the return of the market portfolio. The model's linear specification follows from the assumed joint normality of asset returns. For any security i the market model is

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (3)$$

$$E(\varepsilon_{it} = 0) \qquad \mathrm{var}(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

where R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term. α_i, β_i, and $\sigma^2_{\varepsilon_i}$ are the parameters of the market model. In applications a broad based stock index is used for the market portfolio, with the S&P 500 Index, the CRSP Value Weighted Index, and the CRSP Equal Weighted Index being popular choices.

The market model represents a potential improvement over the constant mean return model. By removing the portion of the return that is related to variation in the market's return, the variance of the abnormal return is reduced. This in turn can lead to increased ability to detect event effects. The benefit from using the market model will depend upon the R^2 of the market model regression. The higher the R^2 the greater is the variance reduction of the abnormal return, and the larger is the gain.

C. *Other Statistical Models*

A number of other statistical models have been proposed for modeling the normal return. A general type of statistical model is the *factor model*. Factor models are motivated by the benefits of reducing the variance of the abnormal return by explaining more of the variation in the normal return. Typically the factors are portfolios of traded securities. The market model is an example of a one factor model. Other multifactor models include industry indexes in addition to the market. William Sharpe (1970) and Sharpe, Gordon Alexander, and Jeffery Bailey (1995, p. 303) provide discussion of index models with factors based on industry classification. Another variant of a factor model is a procedure which calculates the abnormal return by taking the difference between the actual return and a portfolio of firms of similar size, where size is measured by market value of equity. In this approach typically ten size groups are considered and the loading on the size portfolios is restricted to unity. This procedure implicitly assumes that expected return is directly related to market value of equity.

Generally, the gains from employing multifactor models for event studies are limited. The reason for the limited gains is the empirical fact that the marginal explanatory power of additional factors the market factor is small, and hence, there is little reduction in the variance of the abnormal return. The variance reduction will typically be greatest in cases where the sample firms have a common characteristic, for example they are all members of one industry or they are all firms concentrated in one market capitalization group. In these cases the use of a multifactor model warrants consideration.

The use of other models is dictated by data availability. An example of a normal performance return model implemented in situations with limited data is the market-adjusted return model. For some events it is not feasible to have a pre-event estimation period for the normal model parameters, and a market-adjusted abnormal return is used. The market-adjusted return model can be viewed as a restricted market model with α_i constrained to be zero and β_i constrained to be one. Because the model coefficients

are prespecified, an estimation period is not required to obtain parameter estimates. An example of when such a model is used is in studies of the under pricing of initial public offerings. Jay Ritter (1991) presents such an example. A general recommendation is to only use such restricted models if necessary, and if necessary, consider the possibility of biases arising from the imposition of the restrictions.

D. *Economic Models*

Economic models can be cast as restrictions on the statistical models to provide more constrained normal return models. Two common economic models which provide restrictions are the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT). The CAPM due to Sharpe (1964) and John Lintner (1965) is an equilibrium theory where the expected return of a given asset is determined by its covariance with the market portfolio. The APT due to Stephen Ross (1976) is an asset pricing theory where the expected return of a given asset is a linear combination of multiple risk factors.

The use of the Capital Asset Pricing Model is common in event studies of the 1970s. However, deviations from the CAPM have been discovered, implying that the validity of the restrictions imposed by the CAPM on the market model is questionable.[2] This has introduced the possibility that the results of the studies may be sensitive to the specific CAPM restrictions. Because this potential for sensitivity can be avoided at little cost by using the market model, the use of the CAPM has almost ceased.

Similarly, other studies have employed multifactor normal performance models motivated by the Arbitrage Pricing Theory. A general finding is that with the APT the most important factor behaves like a market factor and additional factors add relatively little explanatory power. Thus the gains from using an APT motivated model versus the market model are small. See Stephen Brown and Mark Weinstein (1985) for further discussion. The main potential gain from using a model based on the arbitrage pricing theory is to eliminate the biases introduced by using the CAPM. However, because the statistically motivated models also eliminate these biases, for event studies such models dominate.

5. *Measuring and Analyzing Abnormal Returns*

In this section the problem of measuring and analyzing abnormal returns is considered. The framework is developed using the market model as the normal performance return model. The analysis is virtually identical for the constant mean return model.

Some notation is first defined to facilitate the measurement and analysis of abnormal returns. Returns will be indexed in event time using τ. Defining $\tau = 0$ as the event date, $\tau = T_1 + 1$ to $\tau = T_2$ represents the event window, and $\tau = T_0 + 1$ to $\tau = T_1$ constitutes the estimation window. Let $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$ be the length of the estimation window and the event window respectively. Even if the event being considered is an announcement on given date it is typical to set the event window length to be larger than one. This facilitates the use of abnormal returns around the event day in the analysis. When applicable, the post-event window will be from $\tau = T_2 + 1$ to $\tau = T_3$ and of length $L_3 = T_3 - T_2$. The timing sequence is illustrated with a time line in Figure 1.

[2] Eugene Fama and Kenneth French (1996) provide discussion of these anomalies.

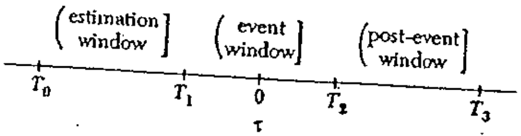


Figure 1. Time line for an event study.

It is typical for the estimation window and the event window not to overlap. This design provides estimators for the parameters of the normal return model which are not influenced by the returns around the event. Including the event window in the estimation of the normal model parameters could lead to the event returns having a large influence on the normal return measure. In this situation both the normal returns and the abnormal returns would capture the event impact. This would be problematic because the methodology is built around the assumption that the event impact is captured by the abnormal returns. On occasion, the post event window data is included with the estimation window data to estimate the normal return model. The goal of this approach is to increase the robustness of the normal market return measure to gradual changes in its parameters. In Section 6 expanding the null hypothesis to accommodate changes in the risk of a firm around the event is considered. In this case an estimation framework which uses the event window returns will be required.

A. Estimation of the Market Model

Under general conditions ordinary least squares (OLS) is a consistent estimation procedure for the market model parameters. Further, given the assumptions of Section 4, OLS is efficient. For the i^{th} firm in event time, the OLS estimators of the market model parameters for an estimation window of observations are

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1} (R_{m\tau} - \hat{\mu}_m)^2} \tag{4}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i \hat{\mu}_m \tag{5}$$

$$\hat{\sigma}^2_{\varepsilon_i} = \frac{1}{L_1 - 2} \sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \tag{6}$$

where

$$\hat{\mu}_i = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{i\tau}$$

and

$$\hat{\mu}_m = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{m\tau}.$$

$R_{i\tau}$ and $R_{m\tau}$ are the return in event period τ for security i and the market respectively. The use of the OLS estimators to measure abnormal returns and to develop their statistical properties is addressed next. First, the properties of a given security are presented followed by consideration of the properties of abnormal returns aggregated across securities.

B. Statistical Properties of Abnormal Returns

Given the market model parameter estimates, one can measure and analyze the abnormal returns. Let $AR_{i\tau}$, $\tau = T_1 + 1, \ldots, T_2$, be the sample of L_2 abnormal returns for firm i in the event window. Using the market model to measure the normal return, the sample abnormal return is

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}. \tag{7}$$

The abnormal return is the disturbance term of the market model calculated on an out of sample basis. Under the null hypothesis, conditional on the event win-

dow market returns, the abnormal returns will be jointly normally distributed with a zero conditional mean and conditional variance $\sigma^2(AR_{i\tau})$ where

$$\sigma^2(AR_{i\tau}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right]. \quad (8)$$

From (8), the conditional variance has two components. One component is the disturbance variance $\sigma^2_{\varepsilon_i}$ from (3) and a second component is additional variance due to the sampling error in α_i and β_i. This sampling error, which is common for all the event window observations, also leads to serial correlation of the abnormal returns despite the fact that the true disturbances are independent through time. As the length of the estimation window L_1 becomes large, the second term approaches zero as the sampling error of the parameters vanishes. The variance of the abnormal return will be $\sigma^2_{\varepsilon_i}$ and the abnormal return observations will become independent through time. In practice, the estimation window can usually be chosen to be large enough to make it reasonable to assume that the contribution of the second component to the variance of the abnormal return is zero.

Under the null hypothesis, H_0, that the event has no impact on the behavior of returns (mean or variance) the distributional properties of the abnormal returns can be used to draw inferences over any period within the event window. Under H_0 the distribution of the sample abnormal return of a given observation in the event window is

$$AR_{i\tau} \sim N(0,\sigma^2(AR_{i\tau})). \quad (9)$$

Next (9) is built upon to consider the aggregation of the abnormal returns.

C. *Aggregation of Abnormal Returns*

The abnormal return observations must be aggregated in order to draw overall inferences for the event of interest. The aggregation is along two dimensions—through time and across securities. We will first consider aggregation through time for an individual security and then will consider aggregation both across securities and through time. The concept of a cumulative abnormal return is necessary to accommodate a multiple period event window. Define $CAR_i(\tau_1,\tau_2)$ as the sample cumulative abnormal return (CAR) from τ_1 to τ_2 where $T_1 < \tau_1 \le \tau_2 \le T_2$. The CAR from τ_1 to τ_2 is the sum of the included abnormal returns,

$$CAR_i(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}. \quad (10)$$

Asymptotically (as L_1 increases) the variance of CAR_i is

$$\sigma_i^2(\tau_1,\tau_2) = (\tau_2 - \tau_1 + 1)\,\sigma^2_{\varepsilon_i}. \quad (11)$$

This large sample estimator of the variance can be used for reasonable values of L_1. However, for small values of L_1 the variance of the cumulative abnormal return should be adjusted for the effects of the estimation error in the normal model parameters. This adjustment involves the second term of (8) and a further related adjustment for the serial covariance of the abnormal return.

The distribution of the cumulative abnormal return under H_0 is

$$CAR_i(\tau_1,\tau_2) \sim N(0,\sigma_i^2(\tau_1,\tau_2)). \quad (12)$$

Given the null distributions of the abnormal return and the cumulative abnormal return, tests of the null hypothesis can be conducted.

However, tests with one event observation are not likely to be useful so it is necessary to aggregate. The abnormal return observations must be aggregated for the event window and across observations of the event. For this aggregation,

TABLE 1

Event Day	Market Model: Good News AR	Good News CAR	No News AR	No News CAR	Bad News AR	Bad News CAR
−20	.093	.093	.080	.080	−.107	−.107
−19	−.177	−.084	.018	.098	−.180	−.286
−18	.088	.004	.012	.110	.029	−.258
−17	.024	.029	−.151	−.041	−.079	−.337
−16	−.018	.011	−.019	−.060	−.010	−.346
−15	−.040	−.029	.013	−.047	−.054	−.401
−14	.038	.008	.040	−.007	−.021	−.421
−13	.056	.064	−.057	−.065	.007	−.414
−12	.065	.129	.146	.081	−.090	−.504
−11	.069	.199	−.020	.061	−.088	−.592
−10	.028	.227	.025	.087	−.092	−.683
−9	.155	.382	.115	.202	−.040	−.724
−8	.057	.438	.070	.272	.072	−.652
−7	−.010	.428	−.106	.166	−.026	−.677
−6	.104	.532	.026	.192	−.013	−.690
−5	.085	.616	−.085	.107	.164	−.527
−4	.099	.715	.040	.147	−.139	−.666
−3	.117	.832	.036	.183	.098	−.568
−2	.006	.838	.226	.409	−.112	−.680
−1	.164	1.001	−.168	.241	−.180	−.860
0	.965	1.966	−.091	.150	−.679	−1.539
1	.251	2.217	−.008	.142	−.204	−1.743
2	−.014	2.203	.007	.148	.072	−1.672
3	−.164	2.039	.042	.190	.083	−1.589
4	−.014	2.024	.000	.190	.106	−1.483
5	.135	2.160	−.038	.152	.194	−1.289
6	−.052	2.107	−.302	−.150	.076	−1.213
7	.060	2.167	−.199	−.349	.120	−1.093
8	.155	2.323	−.108	−.457	−.041	−1.134
9	−.008	2.315	−.146	−.603	−.069	−1.203
10	.164	2.479	.082	−.521	.130	−1.073
11	−.081	2.398	.040	−.481	−.009	−1.082
12	−.058	2.341	.246	−.235	−.038	−1.119
13	−.165	2.176	.014	−.222	.071	−1.048
14	−.081	2.095	−.091	−.312	.019	−1.029
15	−.007	2.088	−.001	−.314	−.043	−1.072
16	.065	2.153	−.020	−.334	−.086	−1.159
17	.081	2.234	.017	−.317	−.050	−1.208
18	.172	2.406	.054	−.263	.066	−1.142
19	−.043	2.363	.119	−.144	−.088	−1.230
20	.013	2.377	.094	−.050	−.028	−1.258

TABLE 1 (*Cont.*)

Constant Mean Return Model					
Good News		No News		Bad News	
AR	CAR	AR	CAR	AR	CAR
.105	.105	.019	.019	−.077	−.077
−.235	−.129	−.048	−.029	−.142	−.219
.069	−.060	−.086	−.115	−.043	−.262
−.026	−.086	−.140	−.255	−.057	−.319
−.086	−.172	.039	−.216	−.075	−.394
−.183	−.355	.099	−.117	−.037	−.431
−.020	−.375	−.150	−.266	−.101	−.532
−.025	−.399	−.191	−.458	−.069	−.601
.101	−.298	.133	−.325	−.106	−.707
.126	−.172	.006	−.319	−.169	−.876
.134	−.038	.103	−.216	−.009	−.885
.210	.172	.022	−.194	.011	−.874
.106	.278	.163	−.031	.135	−.738
−.002	.277	.009	−.022	−.027	−.765
.011	.288	−.029	−.051	.030	−.735
.061	.349	−.068	−.120	.320	−.415
.031	.379	.089	−.031	−.205	−.620
.067	.447	.013	−.018	.085	−.536
.010	.456	.311	.294	−.256	−.791
.198	.654	−.170	.124	−.227	−1.018
1.034	1.688	−.164	−.040	−.643	−1.661
.357	2.045	−.170	−.210	−.212	−1.873
−.013	2.033	.054	−.156	.078	−1.795
.088	1.944	−.121	−.277	.146	−1.648
.041	1.985	.023	−.253	.149	−1.499
.248	2.233	−.003	−.256	.286	−1.214
−.035	2.198	−.319	−.575	.070	−1.143
.017	2.215	−.112	−.687	.102	−1.041
.112	2.326	−.187	−.874	.056	−.986
−.052	2.274	−.057	−.931	−.071	−1.056
.147	2.421	.203	−.728	.267	−.789
−.013	2.407	.045	−.683	.006	−.783
−.054	2.354	.299	−.384	.017	−.766
−.246	2.107	−.067	−.451	.114	−.652
−.011	2.096	−.024	−.475	.089	−.564
−.027	2.068	−.059	−.534	−.022	−.585
.103	2.171	−.046	−.580	−.084	−.670
.066	2.237	−.098	−.677	−.054	−.724
.110	2.347	.021	−.656	−.071	−.795
−.055	2.292	.088	−.568	.026	−.769
.019	2.311	.013	−.554	−.115	−.884

Abnormal returns for an event study of the information content of earnings announcements. The sample consists of a total of 600 quarterly announcements for the 30 companies in the Dow Jones Industrial Index for the five year period January 1989 to December 1993. Two models are considered for the normal returns, the market model using the CRSP value-weighted index and the constant return model. The announcements are categorized into three groups, good news, no news, and bad news. AR is the sample average abnormal return for the specified day in event time and CAR is the sample average cumulative abnormal return for day −20 to the specified day. Event time is days relative to the announcement date.

it is assumed that there is not any clustering. That is, there is not any overlap in the event windows of the included securities. The absence of any overlap and the maintained distributional assumptions imply that the abnormal returns and the cumulative abnormal returns will be independent across securities. Later inferences with clustering will be discussed.

The individual securities' abnormal returns can be aggregated using $AR_{i\tau}$ from (7) for each event period, $\tau = T_1 + 1, \ldots, T_2$. Given N events, the sample aggregated abnormal returns for period τ is

$$\overline{AR}_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau} \qquad (13)$$

and for large L_1, its variance is

$$\mathrm{var}(\overline{AR}_\tau) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma^2_{\varepsilon_i}. \qquad (14)$$

Using these estimates, the abnormal returns for any event period can be analyzed.

The average abnormal returns can then be aggregated over the event window using the same approach as that used to calculate the cumulative abnormal return for each security i. For any interval in the event window

$$\overline{CAR}(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau, \qquad (15)$$

$$\mathrm{var}(\overline{CAR}(\tau_1,\tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} \mathrm{var}(\overline{AR}_\tau). \qquad (16)$$

Observe that equivalently one can form the CAR's security by security and then aggregate through time,

$$\overline{CAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1,\tau_2) \qquad (17)$$

$$\mathrm{var}(\overline{CAR}(\tau_1,\tau_2)) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2(\tau_1,\tau_2). \qquad (18)$$

For the variance estimators the assumption that the event windows of the N securities do not overlap is used to set the covariance terms to zero. Inferences about the cumulative abnormal returns can be drawn using

$$\overline{CAR}(\tau_1,\tau_2) \sim N[0, \mathrm{var}(\overline{CAR}(\tau_1,\tau_2))] \qquad (19)$$

to test the null hypothesis that the abnormal returns are zero. In practice, because $\sigma^2_{\varepsilon_i}$ is unknown, an estimator must be used to calculate the variance of the abnormal returns as in (14). The usual sample variance measure of $\sigma^2_{\varepsilon_i}$ from the market model regression in the estimation window is an appropriate choice. Using this to calculate $\mathrm{var}(\overline{AR}_\tau)$ in (14), H_0 can be tested using

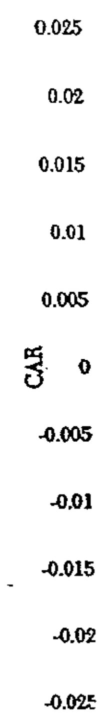
$$\theta_1 = \frac{\overline{CAR}(\tau_1,\tau_2)}{\mathrm{var}(\overline{CAR}(\tau_1,\tau_2))^{1/2}} \sim N(0,1). \qquad (20)$$

This distributional result is asymptotic with respect to the number of securities N and the length of estimation window L_1.

Modifications to the basic approach presented above are possible. One common modification is to standardize each abnormal return using an estimator of its standard deviation. For certain alternatives, such standardization can lead to more powerful tests. James Patell (1976) presents tests based on standardization and Brown and Warner (1980, 1985) provide comparisons with the basic approach.

D. *CAR's for the Earnings Announcement Example*

The information content of earnings example previously described illustrates the use of sample abnormal residuals and sample cumulative abnormal returns. Table 1 presents the abnormal returns av-



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